Open Innovation Norms and Knowledge Transfer in Interfirm Technology Alliances:

Evidence from Information Technology, 1980-1999

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Running head: *Open Innovation Norms and Interfirm Knowledge Transfer*, *1980-1999*

Forthcoming:

Advances in Strategic Management, Volume 30:
Collaboration and Competition in Business Ecosystems

March 16, 2013

ABSTRACT

Purpose – *Firms tend to transfer more knowledge in technology joint ventures compared to contractual technology agreements. Using insights from new institutional economics, the chapter explores to what extent the alliance governance association with interfirm knowledge transfer is sensitive to an evolving industry norm of collaboration connected to the logic of open innovation.*

Methodology/approach – *The chapter examines 1,888 dyad-year observations on firms engaged in technology alliances in the U.S. information technology industry during 1980-1999. Using fixed effects linear models, it analyzes longitudinal changes in the alliance governance association with interfirm knowledge transfer, and how such changes vary in magnitude across bilateral versus multipartner alliances, and across computers, telecommunications equipment, software, and microelectronics subsectors.*

Findings – *Increases in industry-level alliance activity during 1980-1999 improved the knowledge transfer performance of contractual technology agreements relative to more hierarchical equity joint ventures. This effect was concentrated in bilateral rather than multipartner alliances, and in the software and microelectronics rather than computers and telecommunications equipment subsectors.*

Practical implications – *An evolving industry norm of collaboration may sometimes make more arms-length governance of a technology alliance a credible substitute for equity ownership, which can reduce the costs of interfirm R&D.*

Originality/value – *The chapter shows that the performance of material practices that constitute innovation ecosystems, such as interfirm technology alliances, may differ over time subject to prevailing institutional norms of open innovation. This finding generates novel implications for the literatures on alliances, open innovation, and innovation ecosystems.*

Key words: open innovation; industry norm of collaboration; technology alliance governance; multipartner alliances; interfirm knowledge transfer; information technology

Since the early 1980s, firms in knowledge-intensive industries such as biopharmaceuticals and information technology have widely increased their activities in the area of what Chesbrough (2003a) calls 'open innovation'. As opposed to closed innovation, open innovation signifies an innovation logic in which firms progressively encourage and engage in research and development (R&D) activities with a variety of external parties (Laursen & Salter, 2006), for example through collaboration with universities and end users (Adams, Chiang, & Starkey, 2001; von Hippel, 2005), corporate venture capital investments (Dushnitsky, 2006), open source projects (Kogut & Metiu, 2001), spinoff ventures (Parhankangas & Arenius, 2003), and technology alliances with competition (Hagedoorn, 2002). Therefore, the success of firms increasingly rests on their ability to manage interactions with a range of different competitors, complementors, and distributors within their innovation ecosystem (Adner, 2006; Kapoor, 2013a; West & Wood, 2013).

With few exceptions, largely limited to descriptive historical accounts at the individual firm or industry levels of analysis (Chesbrough, 2003a; Powell, 1996; Powell & Giannella, 2010), research has typically focused on the different material practices that constitute open innovation (Dahlander & Gann, 2010). But beyond material practices, open innovation also reflects the progressive institutionalization of collaborative norms at the industry level (Pattit, Raj, & Wilemon, 2012). We know comparatively less about the ways in which such broader industry norms condition the optimal organization of the different material practices that constitute innovation ecosystems. Consequently, an important question is how the performance of open innovation practices changes when an industry norm of collaboration evolves.

Firms embedded in innovation ecosystems need to manage their interactions with competitors, complementors, and distributors and so they face critical managerial challenges along a number of performance dimensions (Adner, 2006): How can knowledge transfer to and from competitors be encouraged? How can interdependence with various complementors be managed? How can coordination across stages of the value chain be created and sustained? While answers to all three questions are important in order to understand the performance implications of firms' innovation ecosystems, here, I focus on the first by studying interfirm knowledge transfer in one among a broader possible set of open innovation practices—technology alliances among competitors (Hagedoorn, 2002; Mowery & Teece, 1996). Therefore, the research question I set out to answer is this: *how does knowledge transfer in interfirm technology alliances change when an industry norm of collaboration evolves?*

I address this question in three steps. I begin with the observation that in technology alliances that firms establish to perform joint research and development related to new technologies, products, and processes, interfirm knowledge transfer is likely to be greater when the alliance is governed by a more hierarchical equity joint venture rather than a more arms-length contractual agreement (Oxley & Wada, 2009). Second, I propose that in the U.S. information technology (IT) industry, the empirical context of my study, an *industry norm of collaboration* evolved during 1980-1999, which progressively acted as an institutional reputation and monitoring system. Finally, drawing on Williamson's (1991) 'shift parameter' framework, I develop and test the argument that this industry norm of collaboration represented an institutional shift parameter that disproportionally augmented knowledge transfer in more arms-length contractual agreements relative to more hierarchical equity joint ventures.

Longitudinal analysis of 1,888 dyad-year observations on firms engaged in technology alliances in the U.S. IT industry during 1980-1999 broadly suggests support for the proposition that an industry norm of collaboration moderated the alliance governance association with interfirm knowledge transfer: over time, contractual agreements became significantly more effective as knowledge transfer conduits compared to joint ventures. Motivated both by conceptual differences between bilateral and multipartner alliances and by differences in the proliferation of collaborative norms across several IT subsectors during the study period, the empirical analysis also speaks to two plausible contingencies that add nuance to the aggregated shift parameter effect. First, the benefits of an industry norm of collaboration appear concentrated disproportionally in bilateral rather than multipartner alliances and so particularly bilateral contractual agreements seem to have benefited from an industry norm of collaboration. Second, consistent with the idea that some IT subsectors may have seen a more significant increase in the prevalence and importance of collaborative norms during 1980-1999, the shift parameter effect appears concentrated in the software and microelectronics rather than computers and telecommunications equipment subsectors. These results generate conceptual implications for the literatures on alliances, open innovation, and innovation ecosystems. One managerial implication is that an evolving industry norm of collaboration may sometimes make more arms-length governance a credible substitute for equity ownership, thus reducing the costs of interfirm R&D.

CONCEPTUAL BACKGROUND

Technology alliance governance, appropriability hazards, and interfirm knowledge transfer

Technology alliances constitute an important knowledge transfer mechanism because they channel the exchange of technological knowledge between partnered firms (Gomes-Casseres, Hagedoorn, & Jaffe, 2006; Mowery, Oxley, & Silverman, 1996; Oxley & Wada, 2009; Rosenkopf & Almeida, 2003; Stuart & Podolny, 1999). In this study, I define interfirm knowledge transfer as the process through which the technological knowledge of one firm is learned and applied by another firm, as reflected in changes within the latter’s knowledge stock (Argote, McEvily, & Reagans, 2003; Darr & Kurtzberg, 2000).

Several studies suggest that the governance structure of technology alliances may influence interfirm knowledge transfer (Mowery et al., 1996; Oxley & Wada, 2009). The governance structure of alliances is important because it sets the conditions within which the partner firms can manage their relationship effectively (Oxley, 1997). Governance structures range from more arms-length contractual agreements between independent firms to more hierarchical equity-based joint ventures in which the partner firms "share ownership of the assets and derived revenues and, thus, share monitoring and control rights" (Kogut, 1988: 175). From a transaction cost economics perspective, the optimal governance structure is the one that most competently addresses the contracting hazards of a given transaction (Oxley, 1997; Pisano, 1989). Absent notable contracting hazards, the default governance structure for an interfirm alliance is a contractual agreement, but when contracting hazards increase, an alliance may be more effectively governed by an equity joint venture (Oxley, 1997; Sampson, 2004).

The primary contracting hazards in technology alliances are appropriability hazards, the hazards associated with the leakage of valuable intellectual property (Oxley, 1997; Teece, 1986). The use of a contractual agreement for the development and transfer of technological knowledge requires specification of the relevant property rights, and the monitoring and control mechanisms that support partners' cooperation *ex post*. This may be problematic for at least two reasons. First, *ex ante* specification of a firm's knowledge and know-how would effectively allow an alliance partner to acquire it without cost (Arrow, 1962: 615). Second, a technology alliance is formed to create new technologies, products, and processes—any of which by definition do not exist at the time of contracting and so a better understanding of the contracted assets will only develop during the collaboration.

Therefore, the inherent uncertainty and ambiguity in technology alliances will complicate adequate specification of contracts. Transaction cost economists thus argue that compared to a contractual agreement, a joint venture promotes greater cooperation and knowledge transfer between partnered firms because shared ownership helps align their incentives (Oxley & Wada, 2009). Moreover, because a joint venture is a separate legal and physical entity with a joint management board and administrative controls, and because of enhanced disclosure requirements (Pisano, 1989), it allows the partner firms to monitor and control the appropriation of technological knowledge (Kogut, 1988). Therefore, knowledge transfer should be greater in joint ventures compared to contractual agreements (Mowery et al., 1996; Oxley & Wada, 2009).

The importance of industry norms

The baseline expectation that equity joint ventures are associated with greater interfirm knowledge transfer than contractual agreements is agnostic about the industry environment within which partnered firms are embedded. However, firms perform their technology alliance activities against the backdrop of an evolving institutional environment that provides "a set of fundamental…ground rules" (Davis & North, 1971: 6). Institutional theories argue that industry norms represent one key set of ground rules that prescribe expectations about firms' patterns of behavior (Scott, 2001). As Scott notes, "normative elements involve the creation of expectations that introduce a prescriptive, evaluative, and obligatory dimension into social life" (2003: 880). A prevailing norm expresses the ultimate value attitudes held by individual actors, which then form the basis for "positive or negative sanctions that reinforce obedience to the institutional norm" (Coleman, 1990: 334). Therefore, normative conformity may be an important source of reputation and legitimacy when firms are subject to the sanctioning mechanisms associated with industry norms (Fauchart & von Hippel, 2008).

Beyond arguing that macro-level industry norms may motivate firms to portray certain desirable behaviors, theoretical work in new institutional economics has suggested that an industry norm may represent a 'shift parameter' that can interact with micro-level institutional arrangements, such as governance structures in technology alliances, in shaping the benefits firms will reap from their transactions (Williamson, 1991). By this logic, it is reasonable to imagine that the alliance governance association with interfirm knowledge transfer may differ subject to prevailing industry norms. This observation is critical to the extent that such industry norms change over time, in which case the optimal organization of otherwise identical technology alliances may differ depending on the period in which they occur. Building on this insight, in what follows I will situate my focus on knowledge transfer in technology alliances within the empirical context of my study—the U.S. information technology industry during 1980-1999—to develop the argument that an evolving industry norm of collaboration has shifted knowledge transfer performance from more towards less hierarchical alliance governance structures.

An industry norm of collaboration in IT, 1980-1999

An industry norm of collaboration is one industry norm that has emerged during the past several decades, especially within knowledge-intensive industries such as biopharmaceuticals and information technology (Pattit et al., 2012: 314-315). It represents an element of the broader logic that Chesbrough (2003a) has labeled 'open innovation', an emergent innovation model in which firms systematically encourage and engage in R&D activities with a range of external actors (Dahlander & Gann, 2010; Laursen & Salter, 2006).

In the U.S., after several decades following World War II characterized by the inward orientation of industrial R&D (Mowery & Teece, 1996), the emergence of an industry norm of collaboration, and more open innovation practices in general, was reflected in a number of developments. For example, the Bayh-Dole Act of 1980 began to permit universities and small businesses to claim ownership of intellectual property associated with federally funded research (Mowery, Nelson, Sampat, & Ziedonis, 2004). It was one of the factors increasing the number and size of industry-university cooperative research centers that stimulated technology transfer between academic institutions and industry (Adams et al., 2001). Not surprisingly, perhaps, the percentage of university research funded by industry rose from about 4% in the 1980s to about 20% during the early 1990s (Cohen, Florida, & Goe, 1994; Rosenberg & Nelson, 1996).

U.S. universities also began creating spinouts at an increasing rate, which progressively created linkages between academia and industry (Mowery et al., 2004). As a consequence, the percentage of new products and processes based on academic research increased during the 1980s and 1990s. Mansfield (1998) presents survey data suggesting that in the information processing industry, the percentage of new products and processes that could not have been developed in the absence of recent academic research rose from 11% (for both products and processes) during 1975-1985 to, respectively, 19% for products and 16% for processes during 1986-1994. Moreover, in the same industry, the average time interval between an academic finding and the commercial introduction of a product or process developed with very substantial aid from such a finding decreased from 6.2 years during 1975-1985 to 2.4 years during 1986-1994.

Beyond a growth in the number and extent of university-industry linkages, a second factor reflecting an emerging industry norm of collaboration is a growth in the level of corporate venture capital (CVC) investments during 1980-1999, especially in sectors such as computers, telecommunications, and semiconductors (Dushnitsky, 2006). The trend in CVC investments paralleled a steep increase in the availability of venture capital more broadly (Gompers & Lerner, 2001). CVC investments are interfirm relationships that allow established firms to tap into emerging technology fields and major IT companies such as Intel, Cisco, and Microsoft were among the largest venturing firms driving this growth. Underlying the explosive growth in CVC investment during the 1980s and 1990s is the fact that among the largest venturing firms during 1969-1999, all IT-related firms except Xerox and Motorola began investing only well after 1980 (Dushnitsky, 2006: 395).

A third development indicative of a mounting trend towards collaboration is firms' increasing engagement with customers (von Hippel, 2005). For example, John Armstrong, former vice president for science and technology at IBM, describes the proliferation of joint projects between IBM researchers and customers (Armstrong, 1996). Involvement of customers, in general, and lead users, in particular, has increased in scale and importance in IT sectors such as microelectronics (custom integrated circuits, see von Hippel, 2005: 127-128) and software, where user communities have increasingly contributed to the development of open-source software (Kogut & Metiu, 2001; Lerner & Tirole, 2002).

A fourth reflection of firms' increasing commitment to open innovation, following a broader wave of corporate refocusing during the 1980s (Davis, Diekmann, & Tinsley, 1994), has been their growing propensity to generate spinoff ventures (Chesbrough, 2003b; Parhankangas & Arenius, 2003). Such spinoffs began to generate networks of knowledge transfer and resource sharing between established and new firms. Spinoffs are consistent with firms' refocusing on their core activities and reducing the scale and scope of internal R&D. During the 1980s the IT industry went through a gradual process of vertical de-integration and towards horizontal organization, which increased the specialization of firms' technological knowledge (Bresnahan & Greenstein, 1999; Langlois, 1990; Macher & Mowery, 2004). Growing specialization was reflected in the increasing distribution of technological knowledge and intellectual property rights across firms. For example, the number of firms performing R&D in the U.S. information technology industry more than doubled between 1986 and 1999, while employment in firms with over 10,000 employees dropped by roughly 30% during 1980-1999 (National Science Foundation, 2010). Moreover, the number of corporate assignees successfully filing IT patents increased from less than 1,000 in 1980 to more than 4,000 in 1999 (Hall, Jaffe, & Trajtenberg, 2002). Therefore, firms became gradually more dependent on others to implement their technological knowledge in integrated solutions.

To this point, examples reflecting an evolving industry norm of collaboration have focused on university-industry collaboration, investment into and creation of new firms, and interaction with users. In all those categories, the IT industry has seen a steady increase in activity during 1980-1999 and so it appears reasonable to imagine that open innovation norms may have become increasingly institutionalized within IT.

A final factor consistent with an evolving industry norm of collaboration, and one particularly central to the thesis of this study, is a steep increase in the number of newly-formed technology alliances (Hagedoorn, 2002). Based on the Cooperative Agreements and Technology Indicators database (CATI, see Hagedoorn, 2002), Figure 1 describes patterns of technology alliance formation in the population of IT technology alliances during 1980-1999.

--- Take in Figure 1 ---

The aggregate number of newly-formed technology alliances increased considerably during this time window, from a few dozen in the early 1980s to several hundreds in the 1990s. This trend reflects, first, the increasingly widespread distribution of technological assets (Hall et al., 2002) as well as changes in the antitrust regime in the U.S. through the National Cooperative Research Act of 1984, which reduced potential antitrust liabilities on research joint ventures and standards development organizations. Second, it is consistent with an increase in the costs of R&D (Hagedoorn, 1993; Mowery & Teece, 1996). Finally, an increase in international competition motivated especially U.S. firms to join their efforts to be able to face a growth in the number of technologically sophisticated competitors internationally (Nelson, 1990). Overall, the result was a steady increase in the connectedness of firms in IT through technology alliances (Cloodt, Hagedoorn, & Roijakkers, 2006, 2010), and the progressive centrality of prominent firms such as IBM, Hewlett-Packard, and Microsoft that began to function as “important mediators in the information flows among different partners” (Cloodt et al., 2006: 738).

Figure 1 also shows that the aggregate alliance formation pattern was characterized by a growth in the prevalence of contractual agreements relative to joint ventures. Moreover, IT technology alliances became increasingly multisectoral—i.e., focused on multiple IT subsectors, such as computers, telecommunications equipment, microelectronics, and software. For example, large manufacturers like IBM began to adapt their technology alliance portfolios towards subsectors such as software to be able to become integrated service providers (Dittrich, Duysters, & de Man, 2007; Hagedoorn & Frankort, 2008). The increase in multisectoral technology alliances reflects the progressive convergence of individual subsectors, sparked in part by evolving interconnections across technologies such as computers, telecom, software, networking, and the Internet (Cloodt et al., 2006; Graham & Mowery, 2003; Mowery & Teece, 1996).

--- Take in Figure 2 ---

The proliferation of technology alliances within IT was also characterized by an increase in the formation of multipartner alliances. Figure 2 shows the number of newly-formed multipartner alliances in IT during 1980-1999. Multipartner alliances became increasingly popular during the 1980s, even though their growth stagnated somewhat during the 1990s. In subsectors such as microelectronics, the early growth of multipartner alliances was in part associated with the formation of the Semiconductor Industry Association (established in 1977) and consortia like SEMATECH (established in 1987), both of which stimulated and legitimized multiparty R&D collaboration (Browning, Beyer, & Shetler, 1995).

Overall, descriptive evidence shows that during 1980-1999, the IT industry witnessed increases in university-industry collaboration, investment into and creation of new firms, interaction with users, and technology alliances among competitors. Paired with the possibility that several open innovation practices may feed on each other—e.g., in the software subsector, Dushnitsky and Lavie (2010) show that alliances may function as an antecedent to their CVC investments and Van de Vrande and Vanhaverbeke (2013) show how the reverse may be true in pharmaceuticals—it is reasonable to suggest that an industry norm of collaboration became progressively institutionalized in IT during 1980-1999. Using Williamson's (1991) shift parameter framework, the following section begins to connect an industry norm of collaboration to the alliance governance association with interfirm knowledge transfer.

An industry norm of collaboration as a shift parameter

Central to Williamson's (1991) shift parameter framework is the assumption that parameters of the institutional environment, such as an industry norm of collaboration, can interact with the institutions of governance, such as governance structures in technology alliances. An industry norm of collaboration is associated with value attitudes of cooperation as the basis for positive and negative sanctioning. I propose that variance in reputational concerns supplies the mechanism connecting an industry norm of collaboration and concomitant value attitudes of cooperation to the knowledge transfer implications of alliance governance. These reputational concerns arise both from the growing importance of a reputation for cooperation and an increasing likelihood that information about firms' reputations spreads in the industry.

First, linkages across firms in IT increased in prevalence and importance during 1980-1999, which reflected both the progressive dependency of firms' businesses on external partnering as well as the growing need to attract new partners in the future. Therefore, relational legitimacy—i.e., the "perceived worthiness as an attractive alliance partner" (Dacin, Oliver, & Roy, 2007: 174)—became more important to partnered firms. Because opportunistic behavior puts firms at risk of compromising their ability to form new alliances in the future, an increasing dependency on collaboration with external parties makes firms more likely to conform actively to behavioral norms associated with appropriate cooperative behavior (Suchman, 1995).

Second, an increase in linkages across firms, in general, and technology alliances among competition, in particular, also generates the possibility that information about a firm's reputation spreads more quickly within the industry. In a relatively disconnected setting, alliance partners operate more or less in isolation, while growing interconnectedness exposes firms to a setting where the amount of information available about potential partners is progressively larger. Because firms draw on their external network to gather information about potential exchange partners (Gulati, 1999), both cooperative as well as opportunistic behaviors are more quickly and accurately communicated when firms are connected to each other through a larger number of direct and indirect linkages (Williamson, 1991: 290-291). Consistent with the idea that greater connectedness in turn reduces the probability of opportunism, Robinson and Stuart (2007) show that equity participation in a strategic alliance between two firms diminishes, and pledged funding increases, when the firms are more proximate in an industry's alliance network.

Overall, an industry norm of collaboration acts as an institutional reputation and monitoring system that establishes the importance of relational legitimacy and shapes firms' ability to find out about others' reputations. Therefore, when a reputation for cooperation becomes more important, the probability of opportunistic behavior is likely to decrease, which is reinforced by the likelihood that reputational information reaches a greater number of actors more quickly (Provan, 1993).

A crucial question remains: does the reputation mechanism associated with an industry norm of collaboration operate differently in contractual agreements compared to joint ventures? Reputational concerns attenuate the probability of opportunistic behavior by alliance partners and should therefore have greater significance in situations where appropriation concerns are more prevalent (Oxley, 1999; Williamson, 1991). All else equal, the transactional hazards associated with the possibility that partners appropriate each other's technological knowledge are greatest in alliances with a limited capacity to monitor and align the incentives of alliance partners—i.e., contractual agreements. In joint ventures, alternatively, the joint management board, administrative controls, and enhanced disclosure requirements allow partner firms to monitor and control the appropriation of knowledge, while shared ownership helps align partners' incentives. Therefore, broader reputational concerns should play a more limited role in joint ventures, where appropriation concerns are less pronounced. Overall, these arguments suggest that an industry norm of collaboration represents an institutional shift parameter whose benefits are concentrated disproportionally in contractual agreements rather than equity joint ventures.

> **Hypothesis 1.** An evolving industry norm of collaboration increases knowledge transfer in technology alliances governed by contractual agreement relative to those governed by equity joint venture.

An industry norm of collaboration should act on the probability of opportunistic behavior depending on the monitoring and incentive alignment capacity of an alliance. Thus, if the number of partners in an alliance affects levels of monitoring and incentive alignment, then the shift parameter effect of an industry norm of collaboration (as summarized in Hypothesis 1) will not be neutral between bilateral and multipartner alliances.

Multipartner alliances embed a collaborative dyad in a cohesive group of interacting firms because they connect partners through multiple reciprocal linkages (Li, Eden, Hitt, Ireland, & Garrett, 2012). By acting as an echo chamber for both positive and negative behaviors of partnered firms, cohesion in a multipartner alliance may act as a monitoring, reputation-inducing, structure that can align the incentives of partner firms. Two firms affiliated to one or more third parties are subject to stronger reputational concerns and the possibility that they will be sanctioned for noncooperative behavior (Burt & Knez, 1995). Multipartner alliances may thus contain a self-enforcing governance mechanism that lowers the value of noncooperative behavior within a dyad. Instead, others have suggested that multipartner alliances may be prone to strategic behaviors such as free riding and coalition building and so the probability of opportunism within a dyad may actually be greater, rather than smaller, when it is embedded in a multipartner alliance (Lavie, Lechner, & Singh, 2007).

Overall, cohesion and opportunism perspectives on multipartner alliances hold opposing views on the incentive properties of multipartner alliances compared to bilateral alliances, with the former arguing for stronger, and the latter for weaker, incentive alignment and monitoring in multipartner compared to bilateral alliances. All else equal, therefore, application of the shift parameter logic to the cohesion perspective suggests that an industry norm of collaboration increases knowledge transfer in bilateral relative to multipartner technology alliances, while the opportunism perspective on multipartner alliances instead suggests that an industry norm of collaboration increases knowledge transfer in multipartner relative to bilateral technology alliances. Integration of these views with the arguments motivating Hypothesis 1 thus generates two rival predictions. Given that monitoring and incentive alignment is weaker in contractual agreements compared to joint ventures, the cohesion perspective suggests that an industry norm of collaboration will have the greatest positive effect on knowledge transfer in bilateral contractual agreements, while the effect will be weakest in multipartner joint ventures.

> **Hypothesis 2a.** An evolving industry norm of collaboration increases knowledge transfer in bilateral technology alliances governed by contractual agreement relative to other technology alliances.

Instead, the opportunism perspective on multipartner alliances suggests that an industry norm of collaboration will have the greatest positive effect on knowledge transfer in multipartner contractual agreements, while the effect will be weakest in bilateral joint ventures.

> **Hypothesis 2b.** An evolving industry norm of collaboration increases knowledge transfer in multipartner technology alliances governed by contractual agreement relative to other technology alliances.

Differences across IT subsectors

Computers, telecommunications equipment, microelectronics, and software are among the prominent IT subsectors to which firms directed their technology alliance activities during 1980-1999. Differentiation in the sectoral emphasis of individual alliances naturally raises the question to what extent alliances focusing on different subsectors were subjected more strongly to an evolving industry norm of collaboration.

In response to the growth of the PC and networking markets, vertically integrated computer and telecommunication equipment manufacturers became more open, but often involving alternative subsectors (Cloodt et al., 2010). For example, when IBM entered the PC market, it did so through a software alliance with Microsoft and a microprocessor alliance with Intel (Malerba, Nelson, Orsenigo, & Winter, 1999). The latter in fact stimulated openness in microelectronics, and not computers, by forcing Intel to share intellectual property related to its microprocessors with second-source suppliers, such as AMD and Fujitsu (Hagedoorn & Schakenraad, 1992; Henkel, Baldwin, & Shih, 2012). Entry by new firms affected both computers and microelectronics subsectors during the 1980s, but established firms in microelectronics were much more active in encouraging such subsector entry through licensing and alliances (Macher & Mowery, 2004). In semiconductors, for example, integrated incumbents began to transact extensively with a large number of specialized, 'fabless', entrants (Kapoor, 2013b). Moreover, in response to intensifying competition from the Japanese semiconductor industry, the Semiconductor Industry Association and consortia such as SEMATECH stimulated progressive collaboration among U.S. semiconductor firms (Browning et al., 1995), and such collaboration became more important with the advent of deep ultraviolet manufacturing technologies in the late 1980s (Iansiti, 1998).

Vertical de-integration in computers was associated with large-scale entry by specialized software producers and, additionally, software radically increased in importance as a general purpose technology (Graham & Mowery, 2003). Because of the gradual commoditization of hardware, and given the growth of mass-markets for 'packaged' software, networked computing, and the Internet, dynamism in the industry amplified as its focus shifted from computer hardware in the early 1980s towards a multitude of software applications in the 1990s. Moreover, as a result of an increasing demand for integrated systems, software has also steeply increased in importance to semiconductor firms since the beginning of the 1990s (Grimblatt, 2002).[1] Underlining the increasing liability of disconnectedness in such a setting, Cloodt et al. note that "to increase their ability to respond very quickly to the changes surrounding them...companies had to remain open innovators" (2010: 125).

This discussion suggests that microelectronics and software subsectors may have seen a more significant increase in the prevalence and importance of open innovation norms during 1980-1999 than computers and telecommunications equipment subsectors. Therefore, the effects as predicted in Hypotheses 1 and 2a/b are likely to be stronger in these two subsectors, though I leave this as an open empirical question. I next examine the shift parameter logic in the context of the U.S. information technology industry, both across and within individual industry subsectors.

METHOD

Data

I use data on technology alliance governance and patenting by firms engaged in technology alliances in the U.S. information technology industry during 1980-1999. Part of the data I use was matched for analyses reported in Gomes-Casseres et al. (2006). The alliance data come from CATI (Hagedoorn, 2002), the patent data come from the NBER patent data file (Hall et al., 2002), and several control variables come from COMPUSTAT. For this study, I added data from CATI, containing information about technology alliances formed since 1960; from USPTO, Osiris, Datastream, the SEC and 10K filings, the U.S. Census Bureau, Eurostat, firms' annual reports, and numerous press releases.

[1] Consistent with the comparative importance of software collaborations, Kapoor (2013a) finds that the collaboration of semiconductor firms with software complementors is more strongly associated with information sharing in R&D and joint product development than collaboration with other complementors.

Three rules combined to determine firms' inclusion in the estimation sample. First, firms needed at least one patent in the IT patent classes in 1980-1999. Second, firms needed at least one technology alliance in IT during 1980-1999. Third, in each dyad, at least one firm needed to be headquartered in the United States. I generated a dyad-year panel to test the refutable implications of the shift parameter logic. In a total of 3,545 dyad-year records, due to a lag specification and missing data on some of the control variables, I have complete data for 1,888 dyad-years, which form the basis for the statistical analyses. The panel is unbalanced, reflecting firms' increasing proclivity to enter into technology alliances during 1980-1999 (Hagedoorn, 2002).

All dyad and firm-level measures are based on yearly adjacency matrices reflecting firms' technology alliance activities within a three-year window. For example, the 1993 matrix contains the alliances for 1991-1993, the 1994 matrix those for 1992-1994, and so on. Specifying an alliance window is important as for many alliances (roughly 90%) termination dates cannot be traced. Further, including alliances only in the formation year would severely underestimate their impact on knowledge transfer between partnered firms. I based the three-year window on the approximately 10% of alliances with traceable duration, as documented in CATI. Left censoring may be a concern for sample firms that were already in business prior to the sampling window. I therefore include the technology alliances formed by the sample firms between 1978 and 1980 in the 1980 adjacency matrix, and those formed in 1979 in the 1981 adjacency matrix.

Dependent variable and analytic strategy

The unit of analysis is the dyad-year and so the empirical models focus on how interfirm knowledge transfer varies over time with the governance of the alliance(s) within a dyadic relationship. Prior research suggests that an aggregated (here: dyad-level) count of the number of patent cross-citations may be a valid indicator of knowledge transfer, in general (Jaffe, Trajtenberg, & Fogarty, 2000), and within the context of interfirm technology alliances, in particular (Frankort, Hagedoorn, & Letterie, 2012: 517-518). While citation-based approaches to interfirm knowledge transfer acknowledge that noise in patent citation measures is unavoidable, they assume that such noise would mainly add measurement error, inflating standard errors, forcing the estimates towards insignificance, and hence producing conservative estimates. However, some evidence suggests that beyond imprecision, patent citation measures may introduce bias as a consequence of citations inserted by patent examiners (Alcácer & Gittelman, 2006), and such bias may actually lead to overstated results. Therefore, I follow Alcácer and Oxley (2013) in using as the dependent variable the overlap in the distribution of firms' patenting activities across technology domains in a given year (Jaffe, 1986). While this measure is based on patents rather than patent citations, consistent with my knowledge transfer definition, it nevertheless captures the notion that convergence in firms' technological activities can be viewed as evidence of interfirm knowledge transfer (Mowery et al., 1996).

I begin with firm-level patent class distribution vectors $\mathbf{F}_{i,t+1} = (F_{i,1,t+1} \ldots F_{i,K,t+1})$ describing firm i's position in technology space in year t+1, where $F_{i,k,t+1}$ is firm i's number of patents successfully applied for in patent class k in year t+1. This generates two yearly vectors for each dyad, describing the distribution of partners' patenting activity across the USPTO's primary patent classes in existence during the sampling period (Hall et al., 2002: 452-453). The technological overlap of partner firms i and j is then calculated as

$$KT_{ij,t+1} = \frac{\mathbf{F}_{i,t+1} * \mathbf{F}'_{j,t+1}}{\sqrt{(\mathbf{F}_{i,t+1} * \mathbf{F}'_{i,t+1}) * (\mathbf{F}_{j,t+1} * \mathbf{F}'_{j,t+1})}},$$

which is the uncentered correlation of the firms' patenting vectors. This measure is bounded by 0 and 1, and values closer to 1 indicate a greater overlap between the patenting activities of firms i and j across technology domains in a given year.

The econometric models focus on the association between the technological overlap measure of interfirm knowledge transfer $KT_{ij,t+1}$ describing a dyadic relationship between two firms i and j in year t+1, and measures of alliance governance, multipartner collaboration, and an industry norm of collaboration in year t—vectors $\mathbf{X}_{ij,t}$ and $\mathbf{X}_t$. Specifically:

$$E(KT_{ij,t+1}) \propto \pi_{ij}\mathbf{X}_{ij,t} + \pi\mathbf{X}_t + \kappa_{ij}\mathbf{X}_{ij,t}\mathbf{X}_t + \tau_{ij}\mathbf{R}_{ij,t} + \gamma_i\mathbf{C}_{i,t} + \gamma_j\mathbf{C}_{j,t} + \phi\mathbf{Y}_t + \nu_{ij}\lambda_{ij,t} + \rho_{ij}Wy_{ij,t} + \delta_{ij}\,,$$

where $\mathbf{R}_{ij,t}$ is a vector of dyad-level control variables; $\mathbf{C}_{i,t}$, $\mathbf{C}_{j,t}$, and $\mathbf{Y}_t$ are vectors of firm and time-period effects, respectively; $\lambda_{ij,t}$ is an inverse Mills ratio; $Wy_{ij,t}$ is a dyad autocorrelation term; and δ_{ij} is a dyad-specific fixed effect. All independent and control variables are lagged by one year to avoid simultaneity. I estimate all models using fixed effects linear specifications.

Alliance governance may be based on firm, dyad, or industry characteristics and so similar factors may determine both alliance governance and interfirm knowledge transfer (Shaver, 1998). From an omitted variables perspective (Heckman, 1979), alliance governance is therefore endogenous in the knowledge transfer equation if key determinants of alliance governance that correlate with interfirm knowledge transfer remain uncontrolled. To capture several such factors, I use a number of control variables and I capture unobserved heterogeneity by including dyadic and time fixed effects, and a dyad autocorrelation variable. Additionally, I use two-stage specifications that account for a selection hazard (Heckman, 1979). To absorb any effects on interfirm knowledge transfer that would otherwise be spurious treatment effects of alliance governance, I include an inverse Mills ratio (i.e., $\lambda_{ij,t}$) constructed from robust probit estimates in the knowledge transfer models. Appendix A details estimation of the probit model.

Independent variables

Technology alliance governance and multipartner collaboration

I use the alliance classification data available in CATI to distinguish non-equity contractual agreements (CATI categories: Joint Research Pacts and Joint Development Agreements) and equity joint ventures (CATI categories: Joint Ventures and Research Corporations). The variable *Joint venture* represents the share of joint ventures in all technology alliances within a dyad in a given year. *Multipartner collaboration* takes the value of '1' in case at least one active technology alliance between two firms has three or more partners.

Industry norm of collaboration

I proxy an industry norm of collaboration using *Industry alliances*, the average number of newly formed IT alliances within the five-year window prior to the observation year. This measure reflects that the norm of collaboration evolved gradually, as captured by a moving average of year-by-year changes in the IT alliance formation series (see Figure 1). While admittedly a moving average of industry alliances is an imperfect proxy for an evolving industry norm of collaboration, estimation of models across subsectors that may have differed in the prevalence and importance of open innovation norms should assuage such a concern.

I test Hypothesis 1 using the interaction between *Joint venture* and *Industry alliances* in the full sample. In subsamples distinguishing contractual agreements (*Joint venture* = 0) and joint ventures (*Joint venture* > 0), I assess the extent to which *Industry alliances*, the shift parameter, has a greater effect on knowledge transfer in contractual agreements compared to joint ventures. I test Hypotheses 2a/b using the interaction between *Joint venture* and *Industry alliances* in subsamples distinguishing bilateral alliances (*Multipartner collaboration* = 0) and multipartner alliances (*Multipartner collaboration* = 1).

Moreover, I examine Hypothesis 1 across IT subsectors by comparing coefficients on the interaction between *Joint venture* and *Industry alliances* in subsector samples for computers and telecommunications equipment, microelectronics, and software. Finally, I examine Hypothesis 2 across IT subsectors by comparing coefficients on the interaction between *Joint venture* and

Industry alliances in subsector samples for computers and telecommunications equipment, microelectronics, and software, after splitting the subsector samples by bilateral alliances (*Multipartner collaboration* = 0) and multipartner alliances (*Multipartner collaboration* = 1).

To capture other macro factors homogeneously shaping the behavior and performance of sampled firms, I include dummies for each two-year period as time fixed effects. Inclusion of yearly dummies would preclude identification of the measure for industry alliances. In subsector analyses split by bilateral/multipartner alliances, I instead include a dummy for the *1990s* to evade collinearity issues associated with two-year dummies, which would otherwise impact the stability of the estimates in several smaller subsamples.

Control variables

Dyad-level control variables

Partner-specific alliances controls for the number of active technology alliances between two firms, while *Partner-specific alliance experience* captures the number of technology alliances between the two partner firms prior to the current three-year window. Moreover, each pair of firms collaborated in one or several IT subsectors. Therefore, I include dummy variables for *Computers/telecom* (as a result of the internet, technologies in computers and telecommunications equipment subsectors virtually merged during the 1990s; see Mowery & Teece, 1996), *Microelectronics,* and *Software*, each taking the value of ‘1’ in case the alliance(s) between two firms concerned activities within these respective IT subsectors. The dummies are not mutually exclusive and so the counterfactual to a dyad’s activity within a particular subsector is activity in zero or more other subsectors.

Firm-level control variables

Firm attributes may influence interfirm knowledge transfer in two distinct ways (Lincoln, 1984: 49-52). First, they index firms’ dispositional tendencies potentially affecting any dyad firms are part of, irrespective of who is the alliance partner. Second, partner firms' attributes may combine to determine knowledge transfer, engendering interaction effects that are dyad specific. To capture dispositional effects, I include the sum of two firms' scores on the respective controls.[2] Collinearity concerns preclude inclusion of the product terms for the firm-level controls in the knowledge transfer models. Because I have no substantive interest in these product terms as such, sole inclusion of the sum terms appears the most reasonable option.[3]

To account for the general alliance experience of the partner firms, I include *Alliance experience* capturing partners' total historical count of technology alliances formed outside the focal dyad until the observation year. I also include *Time in network*, measuring the number of years across which partners' alliance experience had accumulated. I capture firm *Age* as partners' logged age in years since incorporation. Also, because firms differ in size and R&D intensity, I control for firm *Size* by measuring partners' asset value, and *R&D intensity* as the ratio of R&D spending to sales, in a given year. The asset-based firm size control is particularly important because firms that differ in asset intensity may have responded differently to the strengthening of patent rights especially in microelectronics and software, following the Diamond v. Diehr case in 1981 and Texas Instruments' successfully challenging several Japanese and U.S. semiconductor firms in court during 1985-1986 (Hall, 2005; Hall & Ziedonis, 2001).

Firms may be active in multiple dyads simultaneously and, when unaccounted for, this generates dyadic autocorrelation, potentially leading to systematically underestimated standard errors for firm attributes that are constant across multiple dyads within years (Lincoln, 1984). More importantly, such autocorrelation may lead to the misattribution of partners' general

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[2] Rather than including firm-level variables for the partner firms separately, for parsimony I include their sums as covariates (i.e., $[\mathbf{C}_{i,t} + \mathbf{C}_{j,t}]$). While doing so constrains the coefficients on the firm-level variables to equality, results of models in which they are entered separately are largely identical.

[3] Jim Lincoln, personal communication.

proclivity to generate knowledge transfer within their alliances to characteristics of the focal dyad (such as alliance governance). Therefore, I control for *Dyad autocorrelation* (i.e., $Wy_{ij,t}$) as the mean of the dependent variable (technological overlap) for all dyads the partner firms maintained in a given year, but excluding the focal dyad (Lincoln, 1984: 56-61). Because any unobserved, time varying, firm characteristics driving interfirm knowledge transfer within the focal dyad would be manifest in the knowledge transfer within partners' broader set of alliances, this autocorrelation control additionally helps rule out a number of time-varying sources of unobserved heterogeneity at the partner firm level.

RESULTS

Main results

Table 1 shows descriptive statistics for all variables included in the analysis. Table 2 shows estimates for the knowledge transfer models.

--- Take in Tables 1 and 2 ---

Models 1 and 2 in Table 2 present specifications based on the full sample. Model 1 shows the main effect for joint venture. Consistent with prior research, the model suggests that joint venture governance is associated with greater interfirm knowledge transfer than governance by contractual agreement, even after controlling for the endogeneity of alliance governance. All else equal, knowledge transfer—i.e., the subsequent overlap in the distribution of firms' patenting activities across technology domains—is 0.126 units greater in a joint venture compared to a contractual agreement. The coefficient on the multipartner collaboration variable is insignificant. Model 2 turns to an assessment of the shift parameter logic. Consistent with Hypothesis 1, the negative and significant interaction between *Joint venture* and *Industry alliances* suggests that the comparative knowledge transfer performance of joint ventures versus contractual agreements decreases in magnitude at higher levels of industry alliance activity.

Because these estimates are within-dyad, and because in the cross-section an individual alliance cannot at once be a contractual agreement and a joint venture, the interaction term in Model 2 artificially collapses separate longitudinal changes in the different governance structures. For example, the interaction is consistent with an industry norm of collaboration solely increasing knowledge transfer in contractual agreements. It is also consistent with an industry norm of collaboration increasing knowledge transfer in both governance structures, but more so in contractual agreements. To assess these alternatives, Models 3 and 4 present estimates split by individual governance structure. A split-sample approach generates more conservative estimates because it allows residual variance to differ across subsamples (Greene, 2003). In Models 3 and 4, the coefficient for industry alliances is positive and significant for contractual agreements but insignificant for joint ventures. Therefore, it appears reasonable to suggest that an industry norm of collaboration has generated shifts in the knowledge transfer performance of alliances through a disproportionate complementary effect on alliances governed by contractual agreement.

--- Take in Figure 3 ---

The results in Models 3 and 4 are based on fixed effects specifications that impose a within-dyad correlation structure on the data. Therefore, we can interpret the effect of an industry norm of collaboration in Model 3 as acting on knowledge transfer in a contractual agreement moving through 1980-1999. Based on Model 3, Figure 3 shows estimates of knowledge transfer in a contractual agreement during the sampling period, assuming all else equal. The figure shows that knowledge transfer in contractual agreements has increased considerably over time. The conditional effect of industry alliances is 0.065 in 1980, while it is 0.711 in 1999 (see Figure 3). Because the sample standard deviation of technological overlap is 0.192, these estimates suggest that an industry norm of collaboration generated an increase in the knowledge transfer performance of contractual agreements of around 3.4 standard deviations during 1980-1999.

Models 5 and 6 in Table 2 show estimates split by bilateral versus multipartner alliances. Consistent with Hypothesis 2a, the interaction between *Joint venture* and *Industry alliances* is negative and significant in bilateral alliances (Model 5), while it is insignificant in multipartner alliances (Model 6). Therefore, the benefits of an industry norm of collaboration appear concentrated disproportionally in bilateral contractual agreements. Because the reputation mechanism associated with an industry norm of collaboration should act on the probability of opportunistic behavior depending on the monitoring and incentive alignment capacity of an alliance, this result suggests that the baseline probability of opportunism in multipartner alliances is lower than that in bilateral alliances.

It is important to note that the results in Table 2 are unlikely to reflect firms or dyads learning to collaborate and coordinate because they are drawn from models that hold constant a large number of learning correlates (e.g., partner-specific alliance experience, firms' alliance experience, and their network tenure, age, and R&D intensity) and they additionally control for both stable and time-variant dyadic and firm heterogeneity, unobserved temporal effects, and the endogeneity of alliance governance.

Subsector results

The industry alliances measure is an imperfect proxy for an industry norm of collaboration and so I generated a number of additional models split by IT subsector. These models exploit the intuition that different subsectors within IT embraced open innovation at different rates during the sampling window, with the microelectronics and software subsectors expected to have stronger open innovation norms than computers and telecom subsectors. Reputational concerns associated with an industry norm of collaboration should thus be weaker in computers and telecom, and stronger in microelectronics and software subsectors.

--- Take in Table 3 ---

Table 3 shows the subsector estimates for the shift parameter effect as predicted in Hypothesis 1. Because firms within a dyad regularly collaborated in multiple subsectors simultaneously (and increasingly so over time; see Figure 1), the total number of dyad-years across the three subsectors exceeds the sample size of Models 1 and 2 in Table 2. To isolate the effects of open innovation norms within alliances in individual subsectors, dummies for subsectors capture variance in knowledge transfer associated with dyads' simultaneous activities in multiple subsectors. Note that the (marginally) significant computers/telecom dummy captures variance in knowledge transfer associated with a broad sectoral scope in software (Model 9), while the software dummy captures such scope-related variance in computers/telecom (Model 7) and microelectronics (Model 8).

In Models 7-9, the interaction between *Joint venture* and *Industry alliances* is insignificant in computers/telecom (Model 7), negative and marginally significant in microelectronics (Model 8; $p = 0.065$), and negative and significant in software (Model 9). Moreover, the size of the coefficient on the interaction term is more than twice as large (-0.0011 versus -0.0005) in software as in microelectronics, suggesting that the combined effects of alliance governance and an industry norm of collaboration play a much larger role in shaping knowledge transfer in software than in microelectronics. These findings are consistent with the suggestion that open innovation norms within these three IT subsectors differed in prevalence and importance during 1980-1999, with an industry norm of collaboration having a stronger effect in microelectronics rather than computers/telecom, and the strongest effect in software.

--- Take in Table 4 ---

Finally, to examine the idea that an industry norm of collaboration had the most substantive effect in bilateral contractual agreements (see Models 5 and 6 in Table 2), Table 4 shows estimates of the interaction between *Joint venture* and *Industry alliances* in subsector samples split by alliance type (bilateral versus multipartner alliances). Models 10-13 show no significant interaction effect across models of bilateral and multipartner alliances focusing on computers/telecom and microelectronics. In Models 14 and 15, the interaction between *Joint venture* and *Industry alliances* is negative and significant in bilateral software alliances, while it is insignificant in multipartner software alliances.

--- Take in Figure 4 ---

Based on Model 14, Figure 4 shows estimates of the comparative knowledge transfer efficacy of joint ventures relative to contractual agreements in bilateral alliances focused on the software subsector during the sampling period, assuming all else equal. The figure suggests that in software, an emerging industry norm of collaboration dramatically augmented the knowledge transfer benefits of bilateral contractual agreements. The conditional estimates show that in software, bilateral joint ventures generated more than 5.5 times as much knowledge transfer as bilateral contractual agreements in 1980. This comparative efficacy decreased sharply over time, as an otherwise identical joint venture only generated about 1.2 times as much knowledge transfer as an otherwise identical contractual agreement in 1999. Overall, consistent with the results aggregated across subsectors (Models 2-6 in Table 2), the benefits of an industry norm of collaboration appear substantive and concentrated disproportionally in bilateral contractual agreements. Moreover, consistent with the subsector results in Table 3, these effects occur especially in technology alliances within the software subsector.

DISCUSSION AND CONCLUSION

How does knowledge transfer in interfirm technology alliances change when an industry norm of collaboration evolves? I examined this question in some detail within the context of the U.S. information technology (IT) industry during 1980-1999, with a focus on historical changes in the alliance governance association with interfirm knowledge transfer. Descriptive evidence suggests that during the study period, an industry norm of collaboration became progressively institutionalized in IT. I argued that such an industry norm began to act as an institutional reputation and monitoring system that produced incentives for, and reinforced, cooperative rather than opportunistic behavior. Because an industry norm of collaboration should have greater significance in situations where appropriation concerns are more prevalent, application of Williamson’s (1991) shift parameter logic suggests that over time, an evolving industry norm of collaboration has disproportionally increased knowledge transfer in technology alliances governed by contractual agreement relative to those governed by equity joint venture. The empirical analysis broadly corroborates this proposition. Moreover, the shift parameter effect appears particularly concentrated in bilateral rather than multipartner contractual agreements, and in the software and microelectronics subsectors.

First, the assessment of longitudinal change in the alliance governance association with interfirm knowledge transfer complements prior alliance research. Some studies have suggested that the performance effects of alliance governance differ across alliances—e.g., technology, marketing, or production—and across different industries (e.g., Oxley, 1997, 1999; Pisano, 1989; Sampson, 2004). The results of this study additionally suggest that even within one type of alliance and within one industry, the performance and optimal governance of otherwise identical alliances may differ depending on the historical period in which they occur. Therefore, following calls both to exploit the unique insights that longitudinal data can offer (Bergh & Holbein, 1997; Isaac & Griffin, 1989) and to consider the historical context in which firm behavior transpires (Kahl, Silverman, & Cusumano, 2012), this study introduces a historical contingency into prior findings that have often shown effects averaged across time, even in designs spanning several decades (e.g., Gomes-Casseres et al., 2006).

Oxley's (1999) seminal study was among the first to implement Williamson's (1991) shift parameter logic, by connecting theoretically and empirically firms' institutional environment to the governance structure of their alliances. However, as noted by Nickerson and Bigelow, "for inter-firm R&D relationships...the shift parameter framework has yet to be applied to investigate exchange performance" (2008: 192). The current study offers such an application, using the shift parameter framework to evaluate the performance rather than the choice of alliance governance structures (cf. Gulati & Nickerson, 2008). The findings offer fertile ground for further exploration of the longitudinal implications that institutional shift parameters may have for the performance and optimal governance of interfirm alliances. Indeed, governance structures that may appear misaligned with underlying transactional attributes could in fact represent the boundedly rational optimum when viewed through a historical lens that considers relevant changes in the institutional environment. For example, Hagedoorn's (2002; see also Figure 1) observation that technology alliances became progressively governed by contractual agreement especially in uncertain environments appears consistent with an industry norm of collaboration acting on the relative benefits of contractual agreements versus joint ventures.

Second, the introduction of broader norms associated with open innovation into an assessment of the material practices that constitute innovation ecosystems contributes new insight to the open innovation literature. The diffusion of the open innovation logic is reflected not just in the proliferation of a range of material practices, it is also evident in an evolving system of norms that may help govern such material practices. This generates the possibility that as open innovation practices become more prevalent, they at once become less risky and perhaps less costly, by enabling firms to substitute more arms-length governance arrangements for more hierarchical ones. Prior research has devoted considerable attention to exploring institutional differences across nations and industries, and how they shape firm behavior and performance in the area of innovation (e.g., Alexy, Criscuolo, & Salter, 2009; Chesbrough, 1999). Among the implications of such work is the notion that the optimal organization for innovation differs across nations and industries. Complementing these findings, assuming all else equal, the evidence presented here suggests that the optimal organization of innovation activities also varies longitudinally, as open innovation norms evolve at the industry level.

Third, the study shows that an industry-level reputation mechanism acts differentially across different types of alliances. The finding that the shift parameter effect is concentrated in bilateral contractual agreements suggests that appropriability hazards are less pronounced in multilateral joint ventures. This is consistent with the idea that more tightly coupled partners—e.g., those coupled through equity joint ventures, common third parties, or both—have greater control over each other's behavior and are better able to respond to *ex post* behavioral contingencies (Williamson, 1991). Moreover, partner control through tighter coupling appears more important absent institutional mechanisms that bound appropriation concerns, and less so in the presence of such institutional mechanisms.

These findings may extend to the ecosystem level of analysis. For example, Brusoni and Prencipe (2013) suggest that the need for responsiveness and tighter coupling among the members of an ecosystem will be greater in an institutional regime with weak appropriability. This conceptual proposition on the institutional contingency of organizational coupling in ecosystems resonates closely with my empirical findings at the dyadic level of analysis. It thus opens up opportunities for the application of the shift parameter logic to the empirical analysis of interactions between the institutional environment and the prevalence and effectiveness of different types of coupling in innovation ecosystems. Similar to Williamson's (1991) focus on both transactional hazards and the available governance solutions to address such hazards at the transaction level of analysis, Brusoni and Prencipe (2013) discuss both the cooperation and coordination problems that firms in ecosystems may face as well as the solutions that different patterns of organizational coupling can offer to such problems. Thus, their discussion offers a good starting point to begin to think about the theoretical mechanisms through which the institutional environment may affect the difficulty of problems faced by firms in ecosystems, the effectiveness of coupling patterns in addressing such problems, or both.

Fourth, technology alliances are one among a broader set of practices constituting innovation ecosystems, and the transfer of technological knowledge is only one of the relevant performance metrics. The ideas presented and tested here may extend to the study of other aspects of innovation ecosystems. Both the management of interdependence with complementors and coordination with a range of downstream distribution partners generates considerable risks, while dependencies between various complementors may be asymmetric (Adner, 2006; Kapoor, 2013a). For example, Wood and West (2013) illustrate that though Symbian depended fully on its smartphone platform, this was not the case for a large number of complementors in its ecosystem. Therefore, the commitment of individual complementors to the shared success of the ecosystem was unbalanced. In these and other cases, perhaps broader norms can offer an informal source of channel incentives that stimulate multilateral cooperation by aligning the interests of the players in an ecosystem.

Moreover, in a study of the global semiconductor manufacturing industry, Kapoor and McGrath (2012) document how different types of partners—i.e., suppliers, research organizations, and users—may be more or less prevalent in firms' collaboration portfolios across the technology life cycle. It is conceivable that open innovation norms act on all such collaboration types. However, because the prevalence and importance of these partner types may differ over time, it is plausible that at different points in time, broader industry norms may have stronger or weaker effects in collaborations with different types of partners. Also, different norms may act on different stages of the value chain, and interesting questions arise as to how firms' reputations within one stage of the value chain spill over upstream or downstream.

Additional opportunities exist to extend this research as well as address several of its limitations. First, the current analysis is truncated because it disregards the set-up costs of the governance alternatives. A more integrative analysis assesses both the benefits of governance solutions as well as their costs, with the potential to generate a greater understanding of the likelihood that firms substitute one governance structure for another. Second, the focus here has been on contractual agreements and joint ventures, two common modes of governance in technology alliances, and consideration of a broader set of governance mechanisms appears useful. Third, though the study period here reflects one in which open innovation began to evolve, important questions remain about the extent to which there may be limits to the development of collaborative norms associated with open innovation. Finally, Alexy and Reitzig (2013) show how in the mid 2000s, private-collective innovators in infrastructure software coordinated with one another by waiving their exclusion rights so as to establish a broader norm of non-enforcement. This began to expose even proprietary innovators to an unfavorable view of enforcing exclusion rights, generating both reputational benefits to innovators looking for cooperative solutions to intellectual property disputes as well as reputational penalties to those straightforwardly enforcing their property rights. These findings suggest that both the development of norms and their application may be confined to specific open innovation practices, which opens up avenues for a more granular assessment of the enabling and constraining functions of open innovation norms.

The arguments and evidence presented in this study hopefully offer an impetus for further exploration of the interaction between parameters of the institutional environment and the costs and benefits of innovation ecosystems and their constituent open innovation practices.

ACKNOWLEDGEMENTS

I thank volume editors Ron Adner, Brian Silverman, and especially Joanne Oxley for providing detailed feedback and guidance, which has significantly improved the chapter. I am indebted to John Hagedoorn for providing data, and for generously sharing his deep expertise concerning technology alliances in information technology. I also thank Charles Baden-Fuller, Igor Filatotchev, Santi Furnari, Cliff Oswick, Vangelis Souitaris, Andre Spicer, and participants in research and practitioner workshops at Cass Business School for helpful comments and discussion. All errors are mine.

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APPENDIX A: FIRST-STAGE PROBIT MODEL

Table A1 shows robust probit estimates for the choice of alliance governance structure in a firm-partner dyad. I use these estimates to construct an inverse Mills ratio $\lambda_{ij,t}$ for inclusion in the second-stage knowledge transfer models (Heckman, 1979). I model a binary choice in the first stage (i.e., 1 if a dyad contained at least one joint venture, 0 otherwise), even though about 20% of the dyad-years contain more than one alliance. Thus, implicit in my modeling approach is the assumption that most of the endogeneity comes from the decision to use joint ventures at all. Nevertheless, results of two-stage models on dyads containing only one alliance reveal identical results.

--- Take in Table A1 ---

The first instrument is *governance autocorrelation*, which is the mean of the dependent variable (alliance governance structure) for all dyads the partner firms maintained in a given year, but excluding the focal dyad. This instrument takes the same form as the dyad autocorrelation measure in the second stage. Hence, it also addresses autocorrelation in the first stage (Lincoln, 1984: 56-61). Further, since it controls partner firms' baseline proclivities to favor joint ventures over contractual agreements, it also captures otherwise uncontrolled firm heterogeneity. The second instrument is *industry joint ventures*, the share of joint ventures in all newly-formed technology alliances within IT in a given year.

Firms' preference for joint ventures across their technology alliances should correlate positively with the focal dyad containing one or more joint ventures. This may reflect a dominant logic (Lampel & Shamsie, 2000) and perhaps perceptions of competence in managing a particular type of alliance (Levinthal & March, 1993). Such normative organizing principles affect firms' rate of adopting a certain governance structure, while the adoption itself is the more proximate source of any performance consequences. Similarly, the aggregate industry-level preference for joint ventures should correlate positively with the focal dyad containing one or more joint ventures. By institutional theory, firms tend to conform to externally constructed conceptions of legitimate organization (DiMaggio & Powell, 1983) and organizational theorists similarly suggest that a desire to keep pace with competition motivates firms to form ideas about appropriate action based on the actions of others in the industry (March, 1994). Thus, firms are more likely to adopt joint ventures if others in the industry also prefer joint ventures over contractual agreements. It is plausible that governance preferences in partner firms' technology alliance portfolios, and within the industry, will be related to interfirm knowledge transfer only through their impact on dyadic alliance governance, making the exclusion of *governance autocorrelation* and *industry joint ventures* from the knowledge transfer equations valid (Murray, 2006).

In addition to several variables included in the second stage models (Tables 2-4), I followed Lincoln (1984: 49-52) in including product terms for the firm-level controls (alliance experience, size, and R&D intensity) and I include *prior patent cross-citations*, a dyad-specific variable for the number of times two firms had cited each other's patents by the observation year. This additional control captures the depth of the collaboration between partnered firms, and their propensity to draw on each other's technological knowledge base extensively, and should be positively related to equity sharing in a dyadic relationship, all else equal.

The odds that an alliance is governed by a joint venture increase by a multiplicative factor of 5.135 (i.e., exp[1.636]) as my measure of *governance autocorrelation* changes from zero to one. And the odds that an alliance is governed by a joint venture increase by a multiplicative factor of 37.864 (i.e., exp[3.634]) as my measure of *industry joint ventures* changes from zero to one. The likelihood of joint venture governance is thus highly sensitive to both instruments. Moreover, the combined *t*-value of these two variables is 13.349 (i.e., 6.466 + 6.883), suggesting they are jointly relevant as instrumental variables.

The coefficient on *multipartner collaboration* is positive and significant. In a sample of 169 technology alliances commencing in 1996 in the electronics and telecommunications equipment industries, Oxley and Sampson (2004: 741) found similar coefficients on their measure of multipartner collaboration (i.e., *Multilateral*) in models predicting alliance governance structure (see also Sampson, 2004: 510). Such a finding may appear inconsistent with the argument that cohesion in a multipartner alliance acts as a reputation-inducing structure, while it appears consistent with the idea that free riding and coalition building are justified concerns in such alliances. Note that both these arguments focus on the probability of opportunistic behavior. However, even holding constant the probability of opportunism, bilateral and multipartner alliances may be governed by different governance structures because of differences in the interdependence of tasks within each type of alliance (Gulati & Singh, 1998).

It is reasonable to imagine that interdependence may be greater in multipartner alliances, which creates coordination challenges that perhaps require a more hierarchical governance structure. Importantly, this may be the case regardless if the probability of opportunism is low or high. For this reason, we cannot use the governance selection model to infer if bilateral or instead multipartner alliances are subject to a greater probability of opportunistic behavior. In the knowledge transfer models, comparison of interactions between joint venture governance and an industry norm of collaboration across subsamples containing either bilateral or multipartner alliances (Models 5 and 6 in Table 2) offers a more compelling alternative, as an industry norm of collaboration will act narrowly on the probability of opportunistic behavior, and solely as a function of the monitoring and incentive alignment capacity of an alliance rather than its capacity to facilitate coordination.

Fig. 1. Number of newly-formed technology alliances in IT, 1980-1999 (source: CATI)

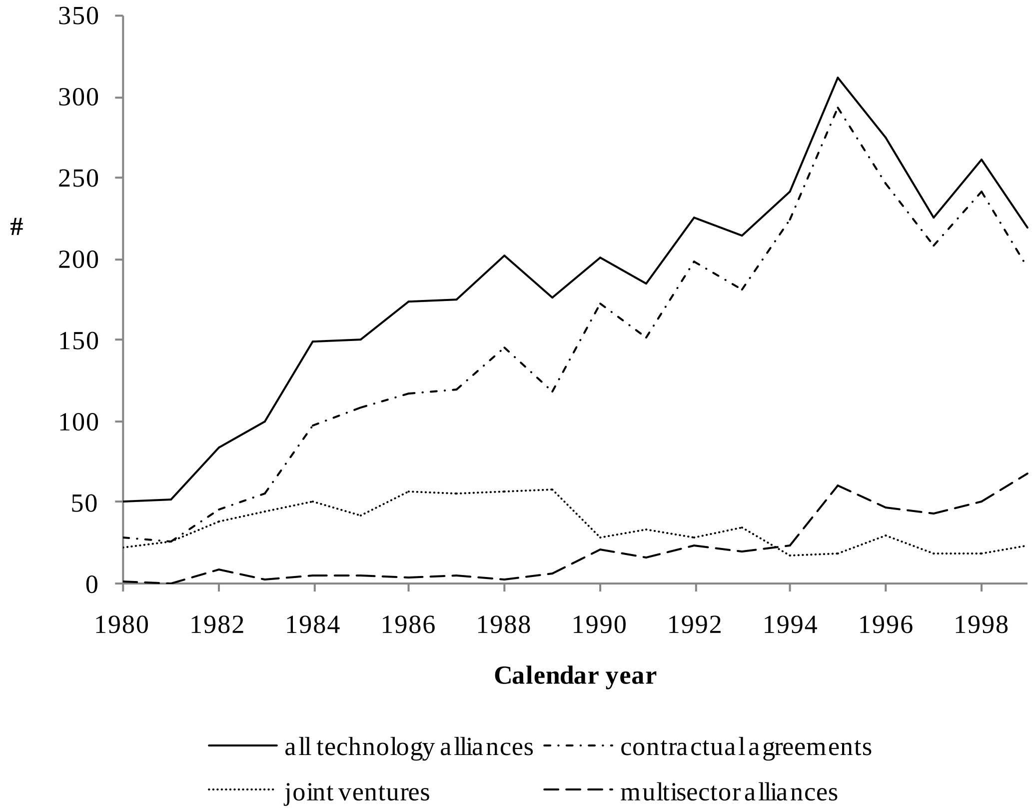

Fig. 2. Number of newly-formed multipartner technology alliances in IT, 1980-1999 (source: CATI)

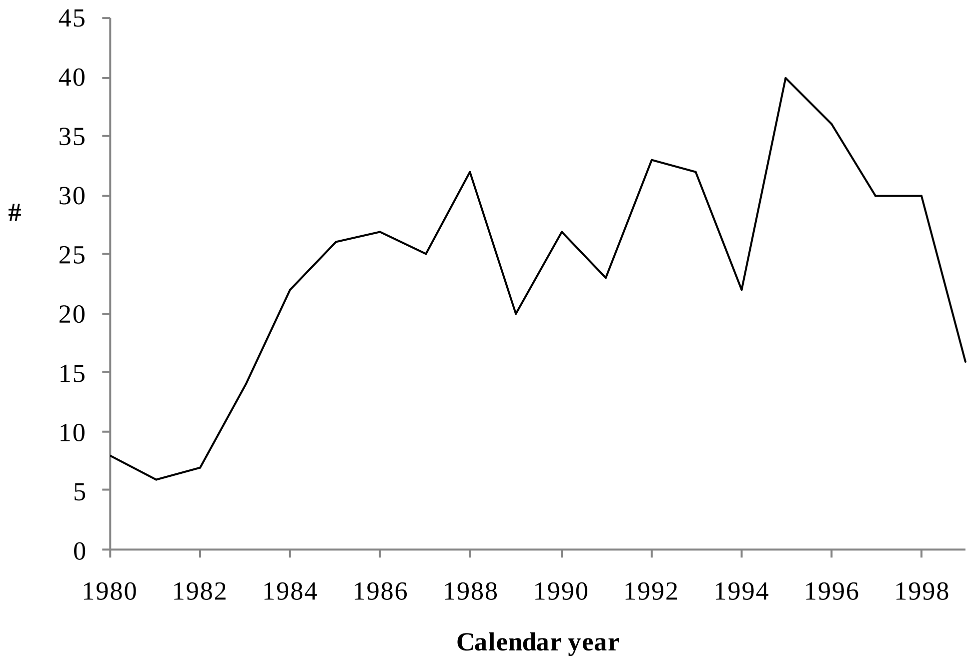

Fig. 3. Estimates of knowledge transfer (technological overlap) in contractual agreements, all else equal, 1980-1999

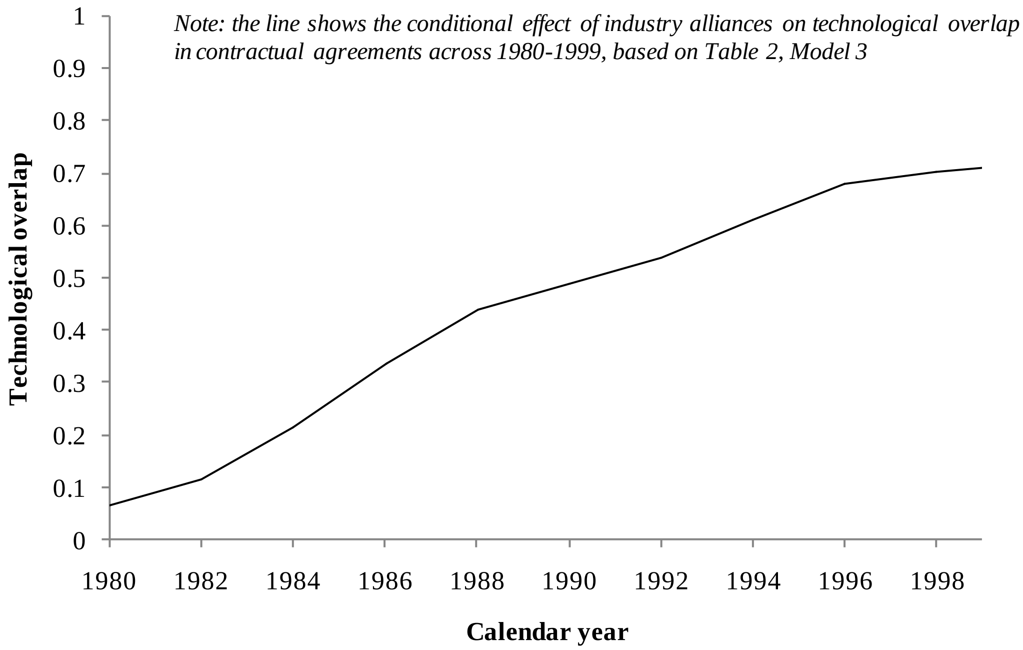

Fig. 4. Estimates of knowledge transfer (technological overlap) in bilateral alliances focusing on software, joint ventures relative to contractual agreements, all else equal, 1980-1999

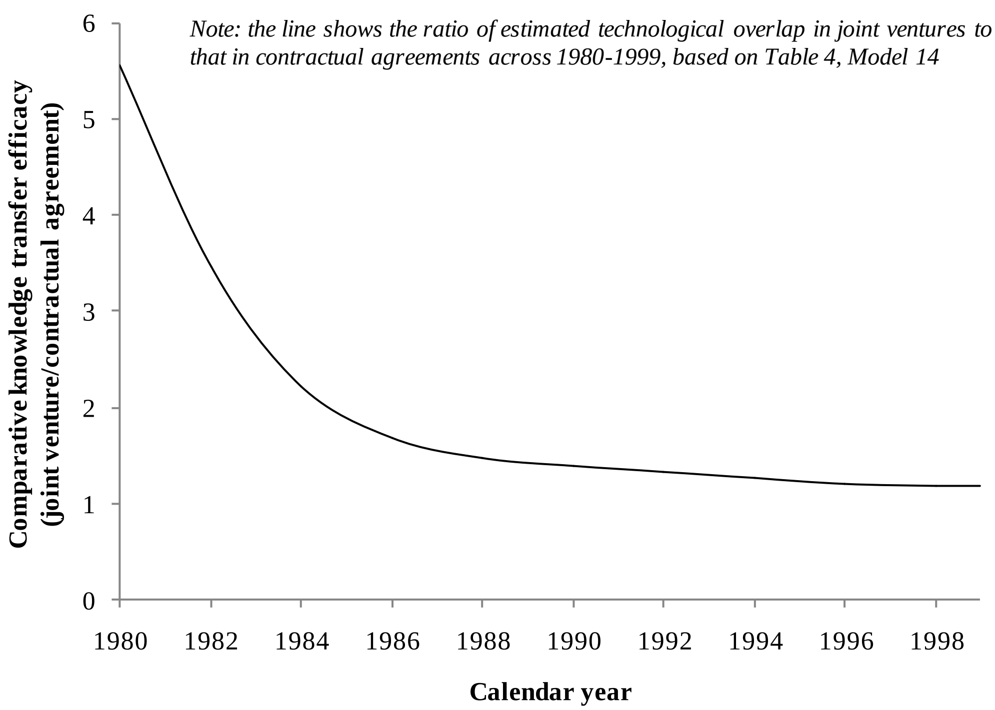

Table 1. Summary statistics (*n* = 1,888)

Variable	Mean	Std. Dev.	Min	Max
Technological overlap	0.167	0.192	0	0.863
Industry alliances	185.567	49.438	22.6	246.6
Joint venture	0.426	0.495	0	1
Multipartner collaboration	0.261	0.439	0	1
Partner-specific alliances	1.396	1.056	1	14
Partner-specific alliance experience	0.777	1.492	0	17
Computers/telecom	0.490	0.500	0	1
Microelectronics	0.540	0.499	0	1
Software	0.297	0.457	0	1
Alliance experience (sum)	83.788	70.306	3	383
Time in network (sum)	19.204	8.229	2	41
Age (sum)	7.339	1.166	3.296	9.915
Size (sum, in millions of U.S. $)	46,180.680	49,734.450	339.000	321,256
R&D intensity (sum)	0.177	0.068	0.022	0.547
Dyad autocorrelation	0.179	0.136	0	0.748
Inverse Mills ratio	0.029	0.602	-3.071	2.488

Table 2. Fixed effects linear models of technology alliance governance and interfirm knowledge transfer in IT, full sample and split by governance structure and number of partners, 1980-1999

	Full sample		Subsamples			
			Contractual agreements	*Joint ventures*	*Bilateral alliances*	*Multipartner alliances*
	(1)	(2)	(3)	(4)	(5)	(6)
Industry alliances	0.002***	0.002***	0.0027***	0.001	0.000	0.001+
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Joint venture	0.126*	0.235***	-	-	0.380***	0.386***
	(0.058)	(0.064)	-	-	(0.043)	(0.087)
Joint venture × Industry alliances	-	-0.001***	-	-	-0.0006***	-0.0007
	-	(0.000)	-	-	(0.000)	(0.000)
Multipartner collaboration	0.008	0.003	0.000	0.001	-	-
	(0.009)	(0.009)	(0.028)	(0.010)	-	-
Partner-specific alliances	-0.003	-0.002	-0.004	-0.001	-0.001	-0.019***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.005)
Partner-specific alliance experience	-0.004	-0.004	-0.012	-0.002	-0.015**	-0.013**
	(0.003)	(0.003)	(0.008)	(0.004)	(0.004)	(0.005)
Computers/telecom	0.008	0.007	-0.002	0.010	-0.002	-0.019
	(0.009)	(0.009)	(0.017)	(0.012)	(0.010)	(0.018)
Microelectronics	0.021*	0.020+	0.021	0.022	-0.004	0.014
	(0.011)	(0.010)	(0.020)	(0.014)	(0.011)	(0.021)
Software	0.012	0.014	-0.013	0.026*	0.009	0.043*
	(0.010)	(0.010)	(0.018)	(0.012)	(0.011)	(0.020)
Alliance experience (sum)	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time in network (sum)	-0.017***	-0.016***	-0.020***	-0.003	0.002+	-0.003
	(0.004)	(0.004)	(0.005)	(0.006)	(0.001)	(0.003)
Age (sum)	0.094***	0.068*	0.068	0.025	-0.034***	-0.033*
	(0.027)	(0.028)	(0.047)	(0.039)	(0.006)	(0.014)
Size (sum)	-0.000*	-0.000+	-0.000	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D intensity (sum)	0.023	-0.041	-0.134	-0.000	-0.115	0.073
	(0.086)	(0.087)	(0.132)	(0.117)	(0.081)	(0.152)
Dyad autocorrelation	0.014	0.016	0.031	-0.024	-0.018	-0.110
	(0.030)	(0.030)	(0.040)	(0.045)	(0.028)	(0.091)
Inverse Mills ratio	-0.018	-0.018	-0.036	-0.010	-0.095***	-0.087**
	(0.012)	(0.011)	(0.028)	(0.014)	(0.014)	(0.030)
Constant	-0.679***	-0.568**	-0.448	-0.224	0.144	-0.113
	(0.206)	(0.206)	(0.339)	(0.314)	(0.114)	(0.184)
Time fixed effects	Y	Y	Y	Y	Y	Y
Dyad-years	1,888	1,888	1,083	805	1,396	492
Unique dyads	581	581	458	126	518	171
R-squared	0.131	0.142	0.128	0.194	0.240	0.281

Standard errors are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1; all tests are two-tailed.

Table 3. Fixed effects linear models of technology alliance governance and interfirm knowledge transfer in IT, split by subsector, 1980-1999

	Subsamples		
	Computers/ telecom	*Micro- electonics*	*Software*
	(7)	(8)	(9)
Industry alliances	0.001	0.001+	0.004***
	(0.001)	(0.001)	(0.001)
Joint venture	0.018	0.116	0.555***
	(0.124)	(0.085)	(0.144)
Joint venture × Industry alliances	-0.0004	-0.0005+	-0.0011*
	(0.000)	(0.000)	(0.000)
Multipartner collaboration	0.009	-0.010	0.007
	(0.015)	(0.012)	(0.020)
Partner-specific alliances	-0.000	0.000	-0.005
	(0.003)	(0.003)	(0.004)
Partner-specific alliance experience	-0.008*	0.010+	-0.008+
	(0.004)	(0.006)	(0.005)
Computers/telecom	-	-0.008	0.031+
	-	(0.017)	(0.018)
Microelectronics	-0.005	-	-0.020
	(0.017)	-	(0.025)
Software	0.026*	0.031+	-
	(0.013)	(0.018)	-
Alliance experience (sum)	-0.001***	-0.000	-0.001*
	(0.000)	(0.000)	(0.000)
Time in network (sum)	0.000	-0.010+	-0.016+
	(0.005)	(0.005)	(0.009)
Age (sum)	0.008	-0.000	0.094
	(0.047)	(0.049)	(0.062)
Size (sum)	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
R&D intensity (sum)	0.000	-0.060	-0.636*
	(0.116)	(0.122)	(0.289)
Dyad autocorrelation	0.043	-0.050	-0.060
	(0.041)	(0.042)	(0.082)
Inverse Mills ratio	-0.006	-0.032	-0.009
	(0.018)	(0.020)	(0.023)
Constant	0.026	0.046	-0.934*
	(0.332)	(0.349)	(0.444)
Time fixed effects	Y	Y	Y
Dyad-years	925	1,019	560
Unique dyads	366	342	179
R-squared	0.171	0.168	0.283

Standard errors are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1; all tests are two-tailed.

Table 4. Fixed effects linear models of technology alliance governance and interfirm knowledge transfer in IT, split by number of partners within subsectors, 1980-1999

	Subsamples					
	Computers/telecom		*Microelectonics*		*Software*	
	Bilateral alliances	*Multipartner alliances*	*Bilateral alliances*	*Multipartner alliances*	*Bilateral alliances*	*Multipartner alliances*
	(10)	(11)	(12)	(13)	(14)	(15)
Industry alliances	0.001*	-0.000	0.003***	0.018	0.004***	0.004+
	(0.001)	(0.002)	(0.001)	(0.013)	(0.001)	(0.002)
Joint venture	-0.025	-	-0.041	-	0.436**	-
	(0.131)	-	(0.094)	-	(0.158)	-
Joint venture × Industry alliances	-0.000	-0.002	0.000	-0.021	-0.001*	-0.000
	(0.000)	(0.002)	(0.000)	(0.013)	(0.000)	(0.002)
Partner-specific alliances	-0.002	-0.005	-0.000	-0.019+	0.002	-0.030**
	(0.004)	(0.007)	(0.004)	(0.011)	(0.006)	(0.010)
Partner-specific alliance experience	-0.007	-0.019**	-0.008	0.005	-0.003	-0.014+
	(0.007)	(0.007)	(0.008)	(0.007)	(0.010)	(0.008)
Computers/telecom	-	-	-0.021	0.003	0.028	-0.051
	-	-	(0.032)	(0.026)	(0.022)	(0.041)
Microelectronics	0.021	-0.119*	-	-	-0.013	-0.106*
	(0.025)	(0.047)	-	-	(0.034)	(0.053)
Software	0.013	0.080	-0.040	0.035	-	-
	(0.016)	(0.049)	(0.031)	(0.024)	-	-
Alliance experience (sum)	-0.001+	0.001	-0.001*	0.000	-0.001	0.001
	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)	(0.002)
Time in network (sum)	-0.006	0.009	-0.023***	0.002	-0.019*	-0.019
	(0.005)	(0.019)	(0.006)	(0.011)	(0.010)	(0.025)
Age (sum)	0.077+	-0.171	0.117*	0.630***	0.138*	-0.730+
	(0.047)	(0.355)	(0.054)	(0.162)	(0.066)	(0.428)
Size (sum)	-0.000+	0.000	-0.000	0.000+	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D intensity (sum)	0.026	-1.571*	-0.445**	0.769**	-0.619+	-0.493
	(0.117)	(0.608)	(0.141)	(0.248)	(0.321)	(0.735)
Dyad autocorrelation	0.065	-0.110	-0.048	0.111	-0.058	-0.292
	(0.041)	(0.214)	(0.046)	(0.133)	(0.086)	(0.326)
Inverse Mills ratio	0.003	0.062	-0.023	-0.011	0.041	-0.025
	(0.029)	(0.062)	(0.023)	(0.074)	(0.033)	(0.056)
1990s	0.043*	0.000	0.043*	-0.065*	0.017	0.037
	(0.021)	(0.000)	(0.020)	(0.025)	(0.037)	(0.122)
Constant	-0.557+	1.780	-0.749*	-4.376***	-1.103*	5.685+
	(0.299)	(2.605)	(0.375)	(1.179)	(0.428)	(3.134)
Dyad-years	808	117	733	286	384	176
Unique dyads	354	57	308	93	135	76
R-squared	0.133	0.401	0.192	0.171	0.233	0.396

Standard errors are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1; all tests are two-tailed.

Note: In the multipartner collaboration subsector samples, there is insufficient within-dyad variance on *Joint venture* and so its main effects are absorbed by dyadic fixed effects. Results of random effects models are similar in signs and significance.

Table A1. Robust probit estimates of alliance governance structure (1 = joint venture; 0 = contractual agreement), 1980-1999

	A.1
Multipartner collaboration	0.795***
	(0.119)
Partner-specific alliance experience	0.302***
	(0.078)
Computers/telecom	-0.480***
	(0.123)
Microelectronics	0.382**
	(0.137)
Software	-0.093
	(0.170)
Prior patent cross-citations	0.005***
	(0.001)
Alliance experience (sum)	-0.002
	(0.002)
Alliance experience (product)	0.000
	(0.000)
Size (sum)	0.000*
	(0.000)
Size (product)	-0.000
	(0.000)
R&D intensity (sum)	0.620
	(1.647)
R&D intensity (product)	35.125+
	(18.407)
Governance autocorrelation	1.636***
	(0.253)
Industry joint ventures	3.634***
	(0.528)
Constant	-2.862***
	(0.343)
Dyad-years	2,540
Log pseudolikelihood	-883.16
Pseudo R-squared	0.482

Robust (dyad clustered) standard errors are in parentheses.

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$; all tests are two-tailed.